Query by Example for Symbolic Still Image Retrieval

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RÉSUMÉ. *Cet article décrit et défini l'utilisation de requêtes par l'exemple (QBE) dans le cadre de recherche symbolique d'images photographiques. La nouveauté de cette approche consiste en l'utilisation conjointe d'indexation symbolique automatique et d'un formalisme de représentation de connaissances pour représenter le contenu des images. De plus, le mécanisme d'abstraction perm la recherche d'images par l'exemple et le bouclage de pertinence basés sur la représentation symbolique des images, et pas sur leur description signal de bas niveau. Nous montrons sur deux collections d'images d'un total de plus de 1100 photographies que la recherche par l'exemple fournit des résultats comparables à ceux par symboles en terme de mesures de rappel-précision.*

ABSTRACT. *This paper defines and studies the use of query by example in the context of symbolic photograph retrieval. The novelty of our approach lies in considering an automatic indexing process of photographs and a knowledge representation formalism to represent the index of images. Moreover an abstraction mechanism process has been developed that allows query by example and relevance feedback based on the symbolic description of images and not directly on their signal-extracted features. We show that on two collections of a total of 1100 photographs the query by example process gives comparable results to textual query in terms of recall and precision measures.*

MOTS-CLÉS :*Indexation Symbolique d'images, Recherche d'Images, Graphes Conceptuels.*

KEYWORDS.*Symbolic Indexing of Images, Image retrieval, Conceptual Graphs.*

1. Introduction

Retrieval of still photographs is a difficult task because we do not really know yet how to accurately link visual features to symbols. That is why the most well known image retrieval systems are based solely on signal features and not on symbols [Smeulder 2000], whereas human beings tend to describe images by words [Jörgensen 1996, 1998]. The problem we consider in this paper is to describe an integrated model which is able to manage several modes of image retrieval based on symbols: queries typed in a term of simple texts, and queries by examples where the user selects examples of the desired photographs in the corpus. One new characteristic of the work described here is that the symbols describing the image are extracted automatically, enabling easy management of huge quantities of data.

A key factor of an information retrieval system requires simple yet accurate interaction. Relevance Feedback (RF) techniques are well known to be simple, because the user need not know all the vocabulary that describes document contents to obtain satisfactory results. RF allows a user to select relevant and/or non-relevant documents from the results of an initial query, and then generates a new query according to the content of the selected documents and the original query. Query By Example (QBE) can be considered a special case of RF, where the initial query retrieves all the documents in the corpus. RF or QBE processing in existing image retrieval systems are mostly based on signal features and not symbols, and there is a mismatch between user's considerations and computer manipulated data. In the work described here, the users as well as the system make implicit use of symbols: the images are indexed using symbols, and when a user wants to retrieve images he thinks with symbols, so the gap between the two actors of the retrieval is narrowed. We know that the automatic generation of image descriptions is subject to uncertainties, and the representation of the image content used in this work manages this parameter in case of automatic indexing. Elements related to the importance of the components of the images are also considered. We study the use of a graph-based description of images content which is automatically generated.

We describe in section 2 the works related to our concern, namely image retrieval systems, relevance feedback and query expansion techniques. In section 3 we focus on the model of images that supports the retrieval. The section 4 is dedicated to the query by example processing. Experimental results on two corpuses are presented in section 5, and we conclude in section 6.

2. Related Works

When considering content-based image retrieval systems, existing approaches differ on the definition of what is "image content":

- The first approach considers as "image content" the raw digital information (i.e. the matrix of pixels). For signal-based indexing, query by example (image or sketch) are extensively used, as the symbolic description of images is not addressed. QBIC [Flickner & al. 1995], VisualSeek [Smith 1996a, 1996b] and BlobWorld [Carson & al. 2002] are example of such systems. They usually incorporate relevance feedback techniques. Our concern here is to allow query by example based both on semantic and feature based description of images. Other works [Meilhac 1999], specifically dedicated to relevance feedback on signal-based descriptions of images, perform well but do not intend to fill the gap between image features and symbols. Queries based on colors and shapes are also supported, but then the execution gulf during the retrieval task [Mulhem 1996] between the user's need and the expression of the query is huge, because the user has to translate his information need into a signal-based description, hoping that the system uses adequate feature matching processes according to his needs.

- The second approach considers the explicit semantic interpretation of images. Among other works, the content description of MPEG-7 [Martinez 2001] and the Dublin Core Metadata Initiative [Weibel 1998] fit into this category. Such approaches take into account the fact that when people describe images [Jörgensen 1996, 1998] they use symbols and not directly signal features. Symbolic-based descriptions are able to manage complex representations [Mechkour 1995, Gupta 1991], but as pointed out in [Rasmussen 1997], symbolic descriptions lack of scalability, are tedious and subject to inconsistencies due to human intervention in the indexing process. In this case, the execution gulf is smaller, and the system has to fill accurately the gap between signal and symbols. Approaches has been done in learning symbols from image feature regions using a priori samples [Town 2000] or relevance feedback [Wood 1998], but in our work we consider that simple lists of labels do not represent adequately image content, hence the use of graphs. Other approaches [Paek 1999, Swets 1996] consider symbolic (mainly keywords) and feature based queries, but do not explicitly link the features to symbolic descriptions, and this lack of information prevents from achieving real combinations between symbols and images features.

If we consider the different ways of providing relevance feedback studied by Koenemann and Belkin [Koenemann 1996], the signal-based systems are mainly able to manage *opaque* RF (i.e. the user selects relevant and/or non-relevant documents and then see the revised ranking). Koeneman and Belkin found out that other relevance feedback interactions, namely *transparent* (the system displays the query generated from the selected document) and *penetrable* (the system allows modification of the generated query before query processing), slightly increased the quality of the results. Transparent and penetrable interactions are only manageable by using symbolic data; this is why we manage to use symbolic descriptions of images, even if the automatic indexing processes on images are not totally accurate.

Our work is also inspired by query expansion on textual documents. Query expansion [Mitra 1998] aims at incorporating additional information in a query coming from external sources or from the documents of the database. Because this work supports symbols, we consider reformulation using user input and other knowledge, namely the hierarchy of concepts that describe the images.

3. The Image Model

The formalism has already been used on photograph content representation [Mechkour 1995]. It has also been shown to be compatible with the inverted file implementation [Ounis 1998]. Conceptual graphs are bipartite finite oriented graphs composed of concept nodes and of relation nodes. Concepts node are composed of a concept type and a referent (generic or individual). A generic referent denotes the existence of a referent, while an individual refers to one instance of the concept type.

The concept types represent the objects of the real world present in the photographs; they are organized in a lattice that reflects generalization/specialization relationships. We defined absolute and relative spatial relationships. Absolute spatial relationships link the image and the object concepts (coming from the labeling process) and indicate the position of the center of gravity by a couple of integers between 0 and 5. Relations are also organized into a lattice.

The weighting scheme is inspired from [Ounis 1999], but we only consider media dependant weights. So, compared to the tf.idf values as defined in [Salton 1983] that models both the importance of a term in the document and with respect to the document collection, we limit ourselves to weights that compute visual term frequencies. We however input the certainty of the recognition of the concepts that is used in our representation. So, we associate one concept with two values:

- The weight *w* of the concept that represents the importance of the concept in the photograph. Many parameters may influence the weight of the objects. We compute the weight of an object as the probability that one pixel of the photograph may be in its region: *w* = surface(region)/surface(image);

- The certainty *c* of recognition of the concept, coming from the labeling process. In case of manual indexing, this certainty is equal to 1.

A concept corresponding to an element of an image is then represented as a [type: referent | w | c]. The Fig. 1 presents a part of the index for one image.

The link between both of the (manual or automatic) labeling system and the representation of the image index is supported by the fact that each of the labels provided by the systems correspond to one concept type in the hierarchy of concepts of the canon.

The input of the labels in the conceptual graph index generates also additional relationships. In our case, the additional relationships generated were used to generate relative and absolute spatial relationships between elements of the image index.

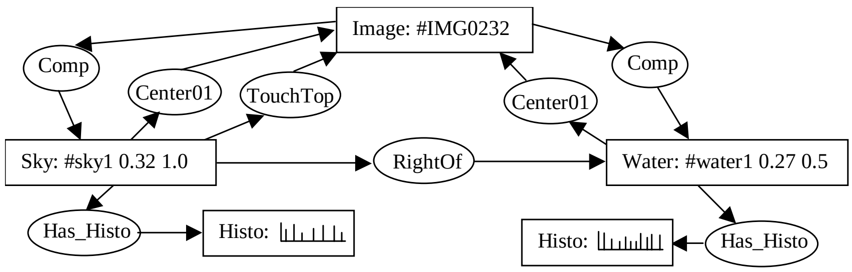


Figure 1. *The Index of an image.*

4. The Query by Example Process

Let us recapitulate that a QBE retrieval interaction process presents a part of the corpus, and then the user is required to choose images that are representative of his need. The system is expected to generate an accurate (compared to the query that could have been input by the user) representation of the users' need from the image contents. The problem is somewhat related to the learning by induction process from a learning sample composed by the image representations. This query generation is achieved by defining a *Compound Least Common Generalizing* (CLCG) graph of the representations of the example images.

For the sake of understanding we will describe the QBE process in two steps:

- We describe first the QBE process on a collection represented by a single concept type. This allows defining the notion of CLCG of concept types;

- We explain then the notion of CLCG of graphs and the additional required steps in order to deal with QBE on images represented by complex graphs (we define a complex graph as a connected graph containing more then one concept).

4.1. *QBE on Simple Graphs*

4.1.1. Compound Least Common Generalization of Concept Types

As described in section 3, concept types and relationships are organized into lattices. For the ease of the explanation, we only use trees instead of lattices for concept type and relation hierarchies in the following. In this part, we consider the concept types presented in Fig. 2. The abbreviation of each concept is between brackets.

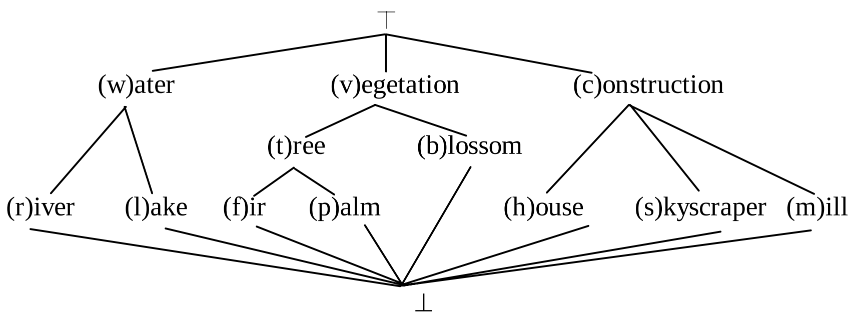


Figure 2 *A concept type hierarchy.*

Consider a corpus of 15 documents (numbered 1 to 15) indexed by graphs composed of only one concept type from the hierarchy of Fig. 1 as described in the last line of Table 1. If a user is looking for photographs containing *tree*s, he should indicate which documents are relevant to his need as shown in Table 1.

Doc Id.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Selected	√	√	√	√	√										
Index	f	f	t	t	V	f	t	b	b	c	b	c	w	w	w

Table 1 *Relevance judgements.*

According to the Table 1, the system should find out that the user focus on *vegetation* and more specifically on *tree*s. We summarize the relevance judgments information by computing the CLCG of the relevant graphs. Because in this part the graphs are limited to a unique concept, we consider CLCG of concept types.

The Least Common Generalization (LCG) of two concept types is the lowest common ancestors of their nodes in a tree hierarchy. Thus we have :

LCG(*tree*,*blossom*) = *vegetation*

We define the CLCG (i.e. Compound LCG) of two trees of concept types T_1 and T_2 as the smallest tree containing T_1, T_2 and the LCG of their roots.

When considering our previous example with simple graphs, we compute iteratively the CLCG tree for each of the marked relevant documents. The corresponding tree for only one concept type *t* is a one node tree containing *t*.

The iterative CLCG of concept types the 6 marked relevant documents considered in their id increasing number is:

$$\mathrm{CLCG(CLCG(CLCG(CLCG(f,f),t),t),v)} = \begin{array}{c} \text{vegetation} \\ | \\ \text{tree} \\ | \\ \text{fir} \end{array}$$

4.1.2. Valuation.

For each of the concept type *t* in the final CLCG, we weight its relevance based on two values:

$$\alpha_t = \frac{|Sel \cap Corpus(t)|}{|Sel|} \qquad \beta_{tq} = \frac{|(Viewed \setminus Sel) \cap Corpus(t)|}{|Viewed \setminus Sel|}$$

- αt is the trend for selected documents (Sel) to be indexed by the concept type t, where Corpus(t) is the set of documents indexed by t, and Sel is the set of documents marked relevant;

- βt is the trend for not selected graphs to contain t, where Viewed is the set of visualized documents during the selection processed. Thus $\beta t/\alpha t$ is as a measure of the significance of the selection of t

Finally the estimated wish to retrieve a concept type *t* is expressed as:

$$wish(t) = u(\alpha_t)\ .\ v\left(\frac{\beta_t}{\alpha_t}\right)$$

where *u* and *v* are real functions constrained by the following properties:

- A concept t_q whose presence in the selected graphs is weak ($\alpha_t \leq 0.5$) is considered not relevant;

- If a concept is more forgotten than selected ($\alpha_t \leq \beta_t$), it is considered as non relevant. Otherwise t_q is almost certainly relevant.

Sigmoid-based functions may be used to generate *u* and *v* (cf. Figure 3):

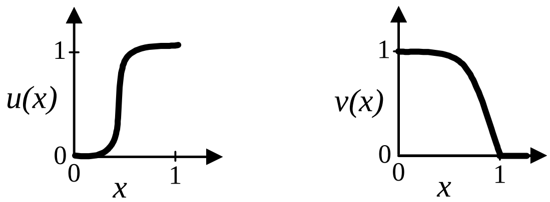


Figure 3 *Shapes of u and v functions.*

Considering our previous example, we obtain the results in Table 2. It appears that [vegetation:*], with a whish value of 0.83, and above all [tree:*] with a wish value of 0.93, are evaluated relevant by the system.

t_q	α_{tq}	β_{tq}	β_{tq} / α_{tq}	wish(t_q)
[vegetation:*]	5/5	5/10	½	$\approx 1 \cdot 0.83 \approx 0.83$
[tree:*]	4/5	2/10	¼	$\approx 0.97 \cdot 0.98 \approx 0.95$
[fir:*]	2/5	1/10	¼	$\approx 0.1 \cdot 0.98 \approx 0.1$

Table 2 *Valuation of a CLCG.*

4.1.3. Matching.

The similarity matching process intends to evaluate the "closeness" between a query CLCG and a concept form a document. This similarity is used during the retrieval of the documents after the selection of relevant documents. The system is then able to rank the results according to the obtained value.

The matching between a query generated as a CLCG T_q and documents that contain a document concept t_d with a weight *w* and a certainty *c* (cf. section 3) is defined as :

$$RSV\ (t_{doc}) = w.c. \max_{t \in T \text{ and } t \text{ ancestor of } t_{doc}} wish\ (t)$$

The similarity of this formula is only computed when one of the more generic concepts of T_q is a generic of the concept t_d, otherwise it's value is zero. This leads to the following similarities according to our example of table 2: RSV(vegetation)=0.83, and RSV(tree)=RSV(fir)=0.95, with *w* and *c* equal to 1. Documents indexed by *tree* are then, as we were expecting, considered more relevant than those indexed by *vegetation*.

4.2. *QBE on Complex Graphs*

We explain now the generalization of what was explained above, in a way to tackle with complex graphs.

4.2.1. CLCG of graphs

Complex graphs are composed of concepts and relations. We explained above how to handle concept types. Relationships are managed in a similar way and CLCG of concept types is easily extended to concepts with referents. However, when dealing with complex graphs the question of which concepts are to be used for the definition of the CLCGs has to be solved.

The following algorithm is used to define CLCG of two graphs *A* and *B*. We call C^X (resp. R^X) the CLCG concepts (resp. relations) of the graph *X*. c^X and r^X are the roots of the CLCG trees C^X and R^X.

- To each concept C^A, we associate all the concepts C^B which minimize $d(c^A, c^B)$: number of nodes between c^A and LCG(c^A, c^B);

- To each R^A belonging to all the subgraphs of pattern $[C^{A\_in}] \rightarrow (R^A) \rightarrow [C^{A\_out}]$, we associate all the relations R^B from the subgraphs of pattern $[C^{B\_in}] \rightarrow (R^B) \rightarrow [C^{B\_out}]$ which minimize d(r^A, r^B), with C^{A_in} and C^{B_in} associated as well as C^{A_out} and C^{B_out}.

- The best substitution between concepts of *A* and *B* is determined by choosing the substitution with:

+ the highest number of association of concepts,

+ if equal, the highest number of association of relations with their concepts *in* and *out* belonging to the substitution,

+ if equal, the maximal following value (where *in* and *out* correspond to the concepts C^{B_in} and C^{B_out} of the second step):

$$\sum_{\substack{\text{concepts of B}\\ \text{in the substitution}}} w.c + \sum_{relations} \sqrt{w_{in} c_{in} \cdot w_{out} c_{out}}$$

- This substitution allows to build the CLCG graph *G* composed of the CLCG concepts CLCG(C^A, C^B) and of the CLCG relations CLCG(R^A, R^B). Concepts and relations from *A* and *B* which do not belong to this substitution are added to *G* in order to keep the whole information of *A* and *B*.

We give an example of the CLCG of four complex graphs:

G_1={[tree]→(close to)→[construction]}, G_2={[fir]→(touch)→[house],

[palm]→(close to)→[lake]}

G_3={[fir]→(touch)→[house], [river]}, G_4={[fir]→(intersect)→[factory], [river]}

Their CLCG is:

$$\left\{ \begin{bmatrix} tree(\frac{4}{4}) \\ | \\ fir(\frac{3}{4}) \end{bmatrix} \rightarrow \begin{pmatrix} \mathrm{intersect}(\frac{4}{4}) \\ | \\ close\,to(\frac{3}{4}) \\ | \\ touch(\frac{2}{4}) \end{pmatrix} \rightarrow \begin{bmatrix} & construction(\frac{4}{4}) & \\ & \swarrow \quad \searrow & \\ house(\frac{2}{4}) & & factory(\frac{1}{4}) \end{bmatrix}, \right.$$

$$\left. \begin{bmatrix} palm(\frac{1}{4}) \end{bmatrix} \rightarrow \begin{pmatrix} close\,to(\frac{1}{4}) \end{pmatrix} \rightarrow \begin{bmatrix} & water(\frac{3}{4}) & \\ & \swarrow \quad \searrow & \\ lake(\frac{1}{4}) & & river(\frac{2}{4}) \end{bmatrix} \right\}$$

The α value of each concept and relation are indicated between brackets.

4.2.2. Valuation.

The process of the valuation for the concepts and relations is similar to what we described above, but we have to keep track of the concepts of the original documents graphs that are used to define the CLCG, in a way to compute α_t and β_t values for concepts and α_r and β_t values for relations.

4.2.2. Matching.

The matching process is very close to the query generation. If *q* is the CLCG obtained by the previous algorithm, CLCG(*q*, *g*) is computed for each graph *g* of the corpus. Only the computation of the score is changed to become RSV_g:

$$RSV_g = \sum_{\substack{concept\, c\, of\, g \\ in\, the\, substitution}} RSV(c) + \sum_{relation\, r} \sqrt{RSV(c_{in}).RSV(c_{out})}.u(\alpha_r)$$

For a relation, the matching value is now weighted by the presence α of the relation in *Sel*.

5. Experiments

5.1. Description

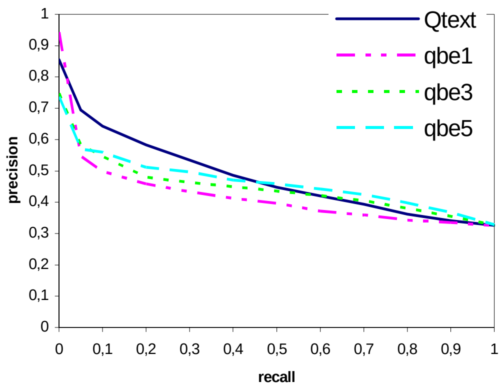
The experiments that evaluate the accuracy of our approach were conducted on two collections representing a total of more than 1100 images. One of the collections is based on gray-level photographs, and the second one on color photographs. The first collection, Col_1, is composed of 498 home photographs automatically indexed according to the work of [Lim 2000]. Because the labeling is automatically generated, the descriptions are not very precise. The number of concept types is 105 and the number of relations is 47. On the collection Col_1, we defined 38 queries involving the labels as well as spatial relationships of labels. An assessment made by 3 persons defined the relevant documents for each query. Query includes objects, relative positions (like "at the left of") and absolute relations (like "touch top").

The second collection, Col_2, is the one used in [Ounis 1998] and is composed of 653 photographs. The number of concepts types is 5945, and the number of relations is 78. The photographs were manually indexed. As we guess according to the complexity of the concept type hierarchy, the descriptions of the photographs are very precise. For the collection Col_2 we do not use any histogram since all the photographs are black and white. The evaluation made for Col_2 is based on 30 queries and on assessments made by 4 people.

5.1. Results

Precision-recall curves in Fig. 4 and 5 show the results obtained for a query built with 1, 3 and 5 examples. The results with a textual query are added so as to compare the QBE process. Relevance of the built query increases with the number of selection. This validates the shape of *u* and *v* functions. As regards to C_1, the

QBE process (average precision of 0.44) is a bit less effective than the textual query process (average precision of 0.46). It is due to the fact that the labeling errors spoil both the built query and the matching process. In the case of a textual input, the labeling errors spoil only one process. For the other corpus (C_2), the QBE results are interesting since the QBE process manages to surpass the textual query performance. The QBE based on 5 documents provides results which are better than or very close to the results obtained using textual queries with an average precision



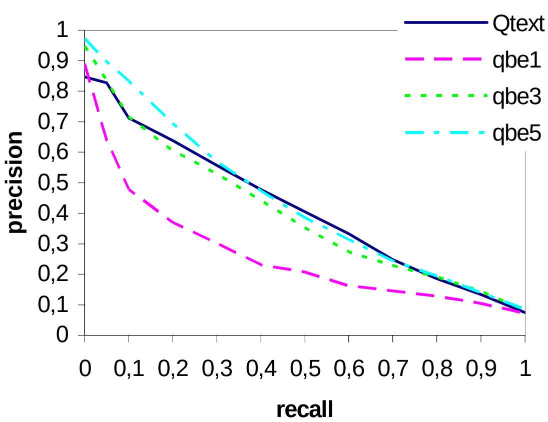
of 0.42 compared to the 0.39 of Qtext.

Figure 4 *Recall/precision curve for the collection C_1.*

Figure 5 *Recall/precision curve for the collection C_2.*

5. Conclusion

We have presented in this paper a way to define Query By Example processes on images described by conceptual graphs. The query generation is based on the indexes of the images selected by a user, and is able to consider the importance of each element (concept as well as relations) in the query, according to their frequency in the selected images index. We considered only positive input because



it is the most useful input mode of query by example.

The results obtained on two collections provide encouraging results. On the automatically indexed collection the QBE process does not perform as well as the textual queries but the gap between these results is not big. For the manually indexed collection, the QBE process outperforms the textual input query results.

The future works are related to expand this approach to include both signal and symbolic indexes of images in a seamless framework. We are targeting to obtain qualitatively similar results, so that users utilize their preferred input mode without impacting the effectiveness of the retrieval system.

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